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| **Newspaper Article Classification Contest** |
| Final Report |

**Terry LiTao Yu**

*tianweil@andrew.cmu.edu taoyu@andrew.cmu.edu*

**Abstract**

This is the final report for the Newspaper Article Classification Contest project. The content includes how we retrieve the features from articles, which classifier we used, how to train the classifier and the performance of our classifier.

**1 Project members**

Terry Li (Andrew ID: tianweil) and Tao Yu (Andrew ID: taoyu)

**2 Feature Extraction**

**2.1 Basic Approach**

We use the word count as the features of our classifier. The process to extract features for train articles and test articles is as below.

Filter Stopwords

Train Docs

Create Dictionary

Filter Stopwords

Get word count

Filter Stopwords

Get word count

Each Doc in Train

Each Doc in Test

Dump to file

Train\_feat.csv

Dump to file

Test\_feat.csv

For each article:

1. Parse the articles and separate it to a bunch of words
2. Remove the stop words
3. Count the word count for each word in the dictionary for each article
4. Use the word count as the features for classification

After filtering the stop words, we have 38800 words left. Then we use these words to classify the articles.

**2.2 Word Stemming**

To reduce the number of features, we leveraged the public Porter Stemming Algorithm [6] to pre-process the documents. After stemming, the number features reduced to 25313.

**2.3 TF-IDF**

To reduce the number of features, we also implemented the tf-idf feature selection algorithm.

The original tf-idf algorithm does not take the class information into account. It only calculates the score of a certain word in a bunch of documents. The original equation is

To introduce the class information into this equation, we used a modified version of tf-idf:

For the tf, the equation is the same:

Because the word count for a certain word in a certain class could be 0, and the doc count that contains a certain word in certain class also could be 0, we introduced add-1 smooth in the process of calculating both tf and idf.

After calculating tf-idf for every feature, we selected 2500 features with the highest scores to be the features of our classifier.

**3 Feature Selection**

**3.1 PCA**

We tried PCA to reduce the number of features. We implemented the PCA in matlab, but it takes lots of time to do diagonal decomposition.

**3.2 l1-based feature selection**

Linear model penalized with the L1 norm have sparse solutions: many of their estimated coefficients are zero. When the goal is to reduce the dimensionality of the data to use with another classifier, we expose a transform method to select the non-zero coefficient.

With logistic-regression, the parameter C controls the sparsity: the smaller C the fewer features selected. With Lasso, the higher the alpha parameter, the fewer features selected.

**4 Naive Bayes Classifier**

For Naïve Bayes classifier,

We use the word count of each to calculate the for every class c.

In the beginning, the equation we used is:

In which is the number of times word appears in the documents in class c.

is the total number of words appears in documents in class c.

Because a certain word may have zero count in a class, then the is 0. This will cause the posterior probability will become 0. Because there are always some words have 0 count in some classes. It makes all posterior probability for every class is 0, which makes our classifier useless.

To solve this problem, we introduced add-1 smooth to the probability calculation. That is we add 1 count for every feature (different word). To make the total probability of all feature still 1, we need to add the number of features to the total word count.

Then the equation becomes:

In which n is the number of features.

For the Prior probability of each class, we just use MLE to calculate them.

After get the and for every word and every class, we finished training the classifier.

**5 Multinomial Naive Bayes**

Multinomial Naive Bayes models the distribution of words in a document as a multinomial. The likelihood of a document is a product of the probability of the words that appear in the document.

So the probability of one document belongs to class c is:

Where the is the frequency of word i in doc.

To simplify the calculation, we use the log likelihood instead of original probability.

Then we can classify the doc into the class that has the highest

**6 Modified Naïve Bayes Classifier**

According to paper [5], the performance of Naïve Bayes Classifier is limited by the prior probability and the probability of word i in each class c . We tried the modification introduced to Naïve Bayes Classifier introduced by paper [5].

**6.1 Complement Naive Bayes (CNB)**

Instead of calculating the probability of word i in class c:

We calculate the probability of word i that is not in class c:

Then the log likelihood of doc belongs to class c is:

**6.2 Transformed Naïve Bayes (TNB)**

Instead of using of as the probability of word i belong to class c, we can also use the tf-idf score of the word i.

Then the log likelihood of doc belongs to class c is:

**7 Support Vector Machine**

We implement a simple version of support vector machine algorithm with kernel parameters of linear, Poly and RBF. For convenience, we choose Quadprog as dual problem solver. We do experiments on linear SVM as well as with RBF kernel as below:

**7.1 Linear SVM**

SVM are shown to handle feature redundancy well, because of the reason that we have 38863 features. It is reasonable to use linear SVM. For features, we use wordcount and TF-IDF features to train the linear SVM model. Every features will contribute to the improvement of the linear SVM model.

C is essentially a regularisation parameter, which controls the trade-off between achieving a low error on the training data and minimising the norm of the weights.

The C parameter tells the SVM optimization how much we want to avoid misclassifying each training example. For large values of C, the optimization will choose a smaller-margin hyperplane if that hyperplane does a better job of getting all the training points classified correctly. Conversely, a very small value of C will cause the optimizer to look for a larger-margin separating hyperplane, even if that hyperplane misclassifies more points. For very tiny values of C, we should get misclassified examples, often even if our training data is linearly separable.

We adjust C from 2^(-10) to 2^5, and find that the accuracy is highest when C is 2^(-10).

**7.2 SVM with RBF kernel**

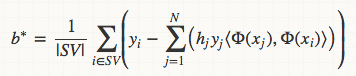
For SVM with RBF kernel, we replace natural product with kernel function. So, at the end, w\*would look like,

Macintosh HD:Users:Nicolas_Yu:Desktop:Screen Shot 2014-05-05 at 9.13.56 PM.png

and hence,

Macintosh HD:Users:Nicolas_Yu:Desktop:Screen Shot 2014-05-05 at 9.14.16 PM.png

Similarly,



and our classification looks like

Macintosh HD:Users:Nicolas_Yu:Desktop:Screen Shot 2014-05-05 at 9.14.37 PM.png

**7.3 SVM Experimental Result**

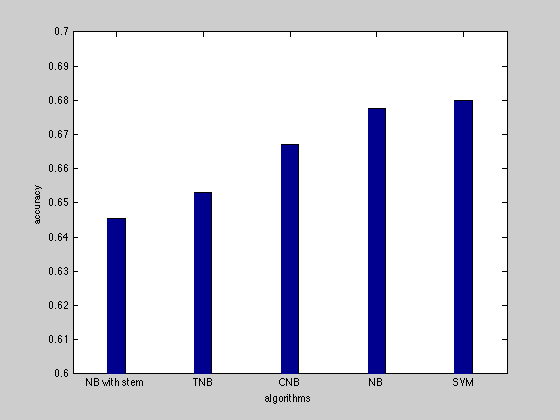
|  |  |  |  |
| --- | --- | --- | --- |
| Feature  Vector Kernel | Kernel Type | Prediction  Success Rate | Kernel Variable |
| wordcount | Linear | 66.88% | C = 2^(-10) |
| TFIDF | Linear | 66.94% | C = 2^(-10) |
| wordcount | RBF | 67.01% | G = 0.5 |
| TFIDF | RBF | 67.05% | G = 0.5 |

Compare wordcount with TFIDF features, TFIDF is a little better than original worcount information.

The experimental results show that SVM consistently achieve performance on text classification tasks. SVMs eliminate the need for feature selection, making the application of text classification easier. Meanwhile, SVM has the advantage of robustness.

**8 Performance**

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| Feature selection method | Accuracy |
| Naïve Bayes with stemming | 64.55% |
| Transformed Naïve Bayes | 65.3% |
| Complement Naïve Bayes | 66.7% |
| Basic Naïve Bayes | 66.75% |
| SVM | 67.05% |



**References**

[1] <http://en.wikipedia.org/wiki/Latent_Dirichlet_allocation>

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[3] Joachims, Thorsten. Text categorization with support vector machines: Learning with

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categorization." ICML. Vol. 97. 1997.

[5] Jason D. M. Rennie, Lawrence Shih, Jaime Teevan, David R. Karger “Tackling the Poor Assumptions of Naive Bayes Text Classifiers”

[6] <http://tartarus.org/martin/PorterStemmer/index-old.html>